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Media coverage and EPA pesticide decisions *

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Abstract. In this paper, we analyze the effect of media coverage on EPA pesticide decisions. We hypothesize that media coverage influences the distribution of opinions in the general public and that EPA decision makers respond to these opinions. We develop a revealed preference model that includes media coverage and public opinion. We test the model by extending the analysis of Cropper et al. (1992) to include media coverage. We find that the media coverage of pesticides has a non-linear effect on EPA pesticide decisions.

1. Introduction

Although the media has been described as the fourth branch of government, empirical studies rarely consider the effect of media coverage on public policy outcomes. The hypothesis that media coverage may influence public opinion, and that public opinion may in turn influence political decision makers, is supported by considerable anecdotal evidence. Consider, for example, the recent history of Uniroyal's Alar (for a detailed account of the Alar controversy, see Yates, 1993). Alar is a plant growth regulator that offers many benefits to apple growers. In 1980, EPA began to review the risks and benefits of Alar to determine if it should be re-approved for use on food crops. Over the next several years, the agency received heavy lobbying pressure from both Uniroyal and the Natural Resources Defense Council (NRDC), the former supporting approval and the latter opposed. Although each interest group had minor victories, neither was dominant, and by 1989 EPA had still not made a binding decision.

In early 1989, NRDC hired a public relations firm to dramatize the potential danger from Alar to sway public opinion strongly in favor of eliminating its use. Utilizing a new scientific study (which subsequently was widely criti-

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cized), along with a famous actress as spokesperson to gain media attention, NRDC brought the chemical to the attention of the press and the public in a very dramatic way. NRDC stressed that the danger to pre-school children from eating apples treated with Alar was intolerable. Alar was referred to as the most potent cancer causing agent in the food supply. Despite this criticism, Uniroyal maintained that Alar was completely safe. The stark conflict between the two sides was enticing to media firms. In March and April of 1989, stories about the Alar were an almost daily feature in newspapers across the country.

As a result of this intense media coverage, it appears that many citizens formed the opinion that Alar was extremely harmful. Sales of red delicious apples, a variety of apple on which Alar was heavily used, dropped dramatically during the period of heavy publicity. Also, some school districts banned apples from children's lunches. Congress, in response to the controversy, introduced a bill that would ban Alar. Faced with a possible congressional ban, Uniroyal withdrew Alar from the market.

The Alar case study illustrates that public opinion may affect the actions of political decision makers. Furthermore, changes in public opinion may be a consequence of media coverage of policy issues. These observations may have implications for a wide variety of political economy models, but in this paper we are primarily concerned with EPA pesticide decisions. In particular, we use a modified revealed preference model to delineate the relationship between media coverage, public opinion, and EPA pesticide decisions.

Revealed preferences models are frequently used to study the behavior of government bureaucracies. The basic theory for these models is presented in McFadden (1975). Although decision making in bureaucracies involves complex interactions among many people, McFadden suggests that it may be useful to assume that the bureaucracy acts as if it is a single decision maker. The decision maker has a stable set of preferences and chooses the action for each decision that leads to the greatest utility. The decision maker's preferences are revealed by observing actual decisions and the characteristics relevant to these decisions, and then estimating a statistical model. McFadden (1976) uses this technique to study freeway route selection in California. Revealed preference models have also been used to study the behavior of the Environmental Protection Agency (Cropper, Evans, Berardi, Ducla-Soares, and Portney, 1992; Gupta, Van-Houtven, and Cropper, 1996; Van-Houtven and Cropper, 1996) the Consumer Product Safety Commission (Thomas, 1988) and the Federal Trade Commission (Weingast and Moran, 1983).

We integrate public opinion and media coverage into a revealed preference model by introducing a decision characteristic called salience. Salience is a measure of the distribution of opinion about the decision in the general public.

It is influenced by media coverage. For example, suppose that the EPA must decide whether or not to ban a pesticide. Media coverage of the pesticide leads some previously uninformed citizens to support the ban and other previously uninformed citizens to oppose the ban. Salience in this case is represented by a two-dimensional vector, with one component equal to the number of citizens that support the ban and the other component equal to the number of citizens that oppose the ban. EPA considers salience (among other things) when making the decision because EPA is supervised by politicians in Congress and the administration, both of whom are sensitive to public opinion. Thus media coverage has an indirect influence on the decision maker through the salience of the decision.

We show that, under appropriate assumptions, the model can be transformed such that media coverage has a direct influence on the decision maker. Information on media coverage, rather than salience, is required for estimation of the transformed model. Using the transformed model, we extend the empirical analysis of Cropper et al. (1992) to include media coverage. We find that coverage of pesticides in the *Washington Post* influences EPA Special Review decisions. We also find evidence that the effect of media coverage is non-linear. The media's influence is very powerful when coverage levels are high.

2. A revealed preference model with salience

Revealed preference models vary depending on the specific situation to which they are applied. They share a basic structure, however, that can be captured with the following example. Suppose that the EPA must decide whether or not to cancel the registration of various pesticides. Let X_i be the vector of observed characteristics relevant to the EPA's decision about the i'th pesticide. Examples of these characteristics include EPA's estimates of the cancer risk to various groups from using the pesticide and the benefits to producers from using the pesticide, as well as the number of interest groups' comments to the EPA during the decision period. The decision maker's preferences are revealed by observing EPA decisions and the corresponding vectors of characteristics and then estimating the following probit model:

$$\text{Probability (pesticide i is canceled)} = \text{Probability}(\alpha X_i + \epsilon_i \geq 0), \quad (1)$$

where α is a vector of unknown coefficients and ϵ_i is a normally distributed error term. Maximum likelihood estimation of (1) yields an estimate of α. We interpret α as the weights used by the decision maker to evaluate the characteristics of the pesticides.

We now extend the revealed preference model given in Equation (1) to include public opinion and media coverage. First consider how media coverage influences the distribution of opinions in the general public. When the media covers a policy issue, some previously uninformed citizens learn about the issue and many of these citizens form an opinion about it. There is a large literature on the characteristics of media coverage of policy issues. (Bennet, 1988: Ch. 2; Graber, 1993: Ch. 4; and Wood, 1985, are good general overviews. Taubes, 1995 discusses media coverage of the Yucca Mountain controversy.) A fundamental observation of this literature is that media coverage tends to polarize issues by introducing and enhancing conflict between opposing sides. Although coverage may be biased toward on one side or the other, it invariably presents both viewpoints. We assume that citizens are influenced by the side that they think is more credible. For pesticide issues, the polarized viewpoints generally come from environmental groups and industry groups. The citizen who grants the claims of an environmental group more credibility is likely to form the opinion that pesticide should be canceled. Other citizens may find the claims of industry more credible, and thus form the opposite opinion. Hence polarized media coverage leads to heterogeneous opinions in the general public.

We use salience to link public opinion to the revealed preference model. To account for heterogeneous opinions, we define a salience vector with two components. Let S_i^f be the number of citizens that are in favor of cancelation of the i'th pesticide and let S_i^a be the number of citizens that are opposed to cancelation. Because salience is influenced by media coverage, we use the following model:

$$S_i^f = g(c_i, z_i) \tag{2}$$
$$S_i^a = f(c_i, z_i), \tag{3}$$

where c_i is media coverage of pesticide i and z_i are other variables that influence opinion. We assume that the functions f and g are stable during the period of a given revealed preference study. Although the details of coverage of individual pesticides may vary, there are stable relationships between coverage and the elements of the salience vector. We expect that both f and g are increasing in media coverage. An increase in coverage leads to a corresponding increase in the number of citizens that have formed an opinion about the pesticide. It is likely that f and g differ in magnitude. For example, suppose that most citizens think that environmental groups are a credible source of information about pesticides. Then media coverage of a given pesticide leads many more citizens to favor cancelation than oppose it.

We expect salience to affect registration decisions because it affects the agency relationship between citizens and politicians. Most registration issues have low salience most of the time due to rational voter ignorance. Agency costs are high. When media coverage increases the salience of a specific issue, the costs of citizens to monitor the decision of the EPA on that issue, and any position taken on it by politicians who control EPA, decreases. In the context of expressive voting by constituents (Brennan and Buchanan, 1984), each politician wants to be seen by constituents to be on the right side of a salient issue. The incentive to be seen that way is strongest for those politicians in Congress and the administration who supervise EPA, because voters may hold them responsible for EPA's actions. Thus, political pressure on EPA, especially from these politicians, should be affected by salience. We expect that such pressure will move in the direction of citizen opinions, when salience affects those opinions.

A modified revealed preference model that includes salience is given by

$$\text{Probability (pesticide i is canceled)} = \text{Probability } (\alpha X_i + \beta S_i^f + \gamma S_i^a + \epsilon_i \geq 0). \quad (4)$$

The two components of the salience vector represent additional characteristics for the decisions. As shown in Equation (4), the decision maker may place different weights on S_i^f and S_i^a. These preferences are revealed by estimating the unknown coefficients α, β and γ. Presumably, the more citizens in favor of cancelation, the more likely it is that the pesticide is canceled, so we expect that $\beta \geq 0$ and $\gamma \leq 0$.

In the model given by Equation (4), the decision maker makes an assessment of S_i^f and S_i^a before making the decision. This assessment may be based on a number of sources such as opinion polls, focus groups, letters, phone calls, etc. In theory, one could estimate (4) directly, but the required information may be difficult to obtain. Alternatively, we can test for the influence of the media, rather than salience, by transforming the model. First, assume that, during the period of a given revealed preference study, either z is constant, or changes in z have no net effect on S_i^f and S_i^a. Then let

$$\eta k(c_i) = \beta S_i^f + \gamma S_i^a = \beta g(c_i) + \gamma f(c_i) \quad (5)$$

where η is an unknown coefficient and k is a function. We can now estimate the following model:

$$\text{Probability (pesticide i is canceled)} = \text{Probability} (\alpha X_i + \eta k(c_i) + \epsilon_i \geq 0), \quad (6)$$

Here media coverage is an explanatory variable in the revealed preference statistical model. If the media variable is significant it indicates the net effect of the media coverage on the decision maker.

The advantage of the model given by Equation (6) is that explicit measures of salience are not required for estimation. The disadvantage is that we can not disentangle the relationship between preferences and salience. Loosely speaking, if η is positive and significant, then the decision maker places more weight on opinions that support cancellation, or the magnitude of g is greater than the magnitude of f, or both. To see this, suppose that $g = \bar{k}f$, where $\bar{k}$ is a constant. It follows that $\eta = \beta\bar{k} + \gamma$.

Media coverage may have a non-linear effect in Equation (6) because the functions f and g, and hence k, may be non-linear. Suppose that there is a bell-shaped distribution for the number of citizens who form an opinion as a function of media coverage. In other words, when coverage is low, only the most impressionable form an opinion; when coverage is high, only the skeptics refuse to join in. It follows that the total number of citizens who form opinions (the integral of the bell-shaped curve up to the given level of coverage) is a logistic function of coverage. We find evidence of non-linearity in the empirical results presented below.

3. Applying the model: EPA pesticide regulation

In the model given by Equation (6), media coverage is a direct influence on the decision maker. To test for the effect of the media, we conduct an empirical study of EPA's regulation of pesticides under the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA). In particular, we extend the work of Cropper et al. (1992) to include the effects of media coverage on pesticide Special Reviews (previously called Rebuttable Presumption Against Registrations). We first replicate the results in Cropper et al. using their data and then perform additional analyses using newly collected data on media coverage.

A Special Review begins when EPA issues a Position Document 1 (PD 1) that delineates the evidence for further investigation of the active ingredient in question. If information collected during the Special Review shows that the initial risk assessment was inaccurate, then the agency issues a PD 2 documenting these results and the Special Review is concluded. If the risks are validated, then the agency issues a PD 2/3. This document contains EPA's assessment of the risks and benefits of the chemical as well as a proposed decision about cancellation. (These assessments may also be subject to political pressures. See Yates, 1997.) The agency then receives comments about its position from a variety of sources: the Scientific Advisory Panel, the Secretary of Agriculture, industry groups, environmental groups, growers, and members of the general public. EPA then makes a final decision about each crop use of the active ingredient and announces this decision, and the end of

Special Review, in the Federal Register. At the same time, it announces the availability of a PD 4 that explains the reasons for its final decision.

3.1. *Statistical analysis*

EPA must decide whether or not to cancel each crop use of a given active ingredient. The revealed preference model is given by Equation (6). The vector of characteristics X_i includes vector of risks and benefits delineated by the PD 2/3. It also includes comments of interest groups. The variable c_i is equal to the media coverage of the active ingredient. Cropper et al. estimate Equation (6) with the implicit restriction that $\eta = 0$. They collected information about EPA assessment of risks and benefits, as well as interest group comments, for 18 active ingredients for which the Special Review was completed and a PD 4 was issued. A list of these ingredients, the corresponding dates for their Special Reviews, and the number crop uses canceled by EPA are shown in Table 1. Overall, these are 242 separate EPA decisions represented in Cropper et al.'s data.

A summary of the variables defined in their data is given in Table 2. The dependent variable, cancel, is defined to equal one if the pesticide was canceled by EPA for a particular crop use and zero otherwise. There are eight risk variables. Three variables indicate the lifetime carcinogenic risk estimates per million persons exposed to the pesticide while mixing it, applying it, or consuming food products on which it was used. Because cancer risk information is sometimes not available, three dummy variables are used to account for missing risk information. There are also dummy variables that indicate whether the pesticide causes adverse reproductive effects or is dangerous to marine life.

The benefits of pesticide use are comprised of three variables. The first variable, producer benefits, is equal to the loss in first year profit sustained by producers if the pesticide was canceled. Since calculating the loss in profit is difficult due to uncertainty about the magnitude of yield losses, EPA does not have quantitative producer benefits data for every decision. Qualitative data on whether or not cancellation of the pesticide would result in yield losses, however, is more readily available. Thus Cropper et al. employ two dummy variables to further represent producer benefits. The benefits missing dummy variable indicates whether or not EPA calculated quantitative estimates of producer benefits. The yield loss dummy variable indicates whether or not their EPA had evidence that yield loss would occur if the pesticide was canceled.

Finally, Cropper et al. measured interest group lobbying pressure from three groups: academics, growers, and environmental groups. A dummy

Table 1. Media coverage and EPA special reviews

Active ingredient	Date announce special review (PD 1)	Date conclude special review (PD 4)	Words in Washington Post		Number uses canceled/ number uses
			Front section	Other sections	
DBCP	9/15/77	9/6/78	4550	4020	12/12
Amitraz	3/30/77	6/4/79	0	0	1/2
Chlorobenzilate	5/14/76	2/5/79	0	0	2/3
Endrin	7/19/76	7/17/79	2310	2640	4/8
Pronamide	5/9/77	10/19/79	830	0	0/4
Dimethoate	9/2/77	1/6/81	0	2180	0/25
Benomyl	11/23/77	10/1/82	0	2960	0/26
Diallate	5/24/77	5/30/82	0	0	0/10
Oxyfluorfen	Jan. 80	6/18/82	0	0	0/3
Toxaphene	5/12/77	11/10/82[a]	6020	2010	7/11
Trifluralin	8/17/79	7/15/82	0	0	0/25
EDB	12/1/77	9/28/83	6885	0	18/18
Lindane	2/8/77	9/30/83	2150	5790	0/8
Silvex	7/9/79	10/14/83[b]	1540	830	6/6
2,4,5-t	4/11/78	10/14/83[b]	20156	11120	2/2
Dicofol	3/4/84	5/22/86	416	0	0/4
Alachlor	1/2/85	12/14/87	4805	0	0/10
Captan	8/6/80	2/16/89	3354	8147	44/65
Totals					96/242

[a] Announced at press conference 10/18/82.
[b] Date of intent to cancel notice.

variable is used for each group to indicate whether or not the group made comments about EPA's proposed decision during the public comment period.

We supplement Cropper et al.'s data by collecting a measure of media coverage. We use the amount of newspaper coverage as a proxy for the level of media coverage of the active ingredient. In particular, we searched for occurrences of the active ingredient in the text of *The Washington Post* during the Special Review period. *The Washington Post* was selected because the full text from 1977 was available in an on-line data base service. The start date (date of the PD 1) and the stop data (date of the PD 4) correspond to the date the Federal Register notice was signed. This usually preceeds the actual publication date by 1–2 weeks. Coverage levels in the *The New York Times* showed a similar pattern, although data were not available for the early pesticide decisions.

Table 2. Summary of data from Cropper et al. (1992)

Cancel	Indicates EPA decision (1 = pesticide was cancelled)
Diet risk	Lifetime cancer risk per million persons exposed to pesticide residue in diet
Diet missing	Indicates whether data on diet risk was available to EPA (1 = data missing)
Applicator risk	Lifetime cancer risk per million persons exposed to the pesticide while applying it to crops
Applicator missing	Indicates whether data on applicator risk was available to EPA (1 = data missing)
Mixer risk	Lifetime cancer risk per million persons exposed to the pesticide while mixing it
Mixer missing	Indicates whether data on mixer risk was available to EPA (1 = data missing)
Reproductive effects	Indicates whether the pesticide exhibits adverse reproductive effects (1 = yes)
Danger to marine life	Indicates whether the pesticide is harmful to marine life (1 = yes)
Producer benefits	Loss in first year profits to producers if pesticide is canceled
Benefits missing	Indicates whether data on producer benefits was available to EPA (1 = data missing)
Yield loss	Indicates whether crop yield loss occurs if pesticide is canceled (1 = yield loss)
Academics comment	Indicates whether academics commented on the pesticide during the public comment period (1 = yes)
Growers comment	Indicates whether grower organizations commented on the pesticide during the public comment period (1 = yes)
Environmental groups comment	Indicates whether environmental groups commented on the pesticide during the public comment period (1 = yes)

We employ two coverage variables. The first (c_f) is equal to the total number of words in all articles that mention the active ingredient and begin in the front section of *The Washington Post*. The second (c_o) is equal to the total number of words in all articles that mention the active ingredient and begin in a non-front section. The coverage figures are shown in Table 1. No attempt was made to distinguish between different crop uses of the same active ingredient; we assume that media coverage affects all decisions in a particular Special Review equally.

It is possible that the level of media coverage is influenced by some of the independent variables in Cropper's analysis. Hence we use a simultaneous equations model. We let $k(c_f)$ represent the measure of media coverage of the special review. In addition to (6) we have

$$c_f = \zeta X + \rho c_o + u, \tag{7}$$

where (ζ, ρ) are unknown coefficients and u is a normally distributed error term. The EPA cancel decision does not influence media coverage because we stopped collecting coverage information on the date when the decision was announced. We are primarily interested in Equation (6), but if ϵ and u are correlated, than c_f and ϵ are correlated, and the probit coefficients are inconsistent. Testing for such correlation requires that we find a variable that influences front section media coverage, but does not influence the EPA decision. As shown by Equation (7), we use media coverage in non-front sections for this purpose.

We would expect the inclusion of the media variable to change the magnitude, but not the signs, of the coefficients in Cropper's analysis. It is difficult to predict the sign of the media variable because it measures the net effect of the media. One could perform content analysis of the articles in *The Washington Post*. (See Baumgartner and Jones, 1993, for a content analysis of titles of pesticide articles from a much broader sample.) But the results would not be definitive, even if the articles appeared to be biased for or against cancellation of the pesticides. For example, suppose that media coverage presents arguments from industry groups and environmental groups and this coverage is biased in favor of the latter. Furthermore, suppose that most of the general public feels that industry groups are a more credible source of information about pesticides and the EPA decision maker places an equal weight on S_i^a and S_i^f. Under these conditions, the media coefficient would be negative, even though media coverage appears to be biased in the opposite direction.

3.2. *Estimation results*

We first test to see if the error terms in Equations (6) and (7) are uncorrelated. In particular, we use Smith and Blundell's (1986) procedure, modified for a probit model, to test the null hypothesis that ϵ and μ are uncorrelated. This hypothesis is not rejected at normal significance levels. Hence we can consistently estimate the probit Equation (6) in isolation.

Equation (6) is estimated using maximum likelihood methods (assuming that $\epsilon_i \sim IN(0, 1)$). The results are shown in Table 3. The first column shows the coefficients when media coverage is not included. This is an exact replication of the results in Cropper et al. Notice that missing information is accounted for by multiplying the variable of interest by the inverse of the appropriate data missing dummy. The data missing dummy variables are also included as independent variables. Thus we interpret the coefficient for the second variable in Table 3 as the effect of diet risk on the cancellation decision, given that information on diet risk is available to EPA. For convenience, we will simply refer to this variable as the diet risk variable. Cropper et al.'s results suggest that EPA does follow the FIFRA mandate to consider both risks and benefits when making the cancellation decision. Increases in producer benefits decrease the probability that the pesticide is canceled. When quantitative estimates of benefits are not available, the existence of qualitative information about yield loss decreases the probability that the pesticide is canceled. Both increases in diet risk and increases in applicator risk lead to increases in the probability that the pesticide is canceled. Evidence of reproductive effects increases the probability of cancellation. Cropper et al. show that the ratio of a cancer risk coefficient to the producer benefit coefficient can be converted into an implicit measure of EPA's value per cancer case avoided. For applicator risk, the implied value per cancer case avoided is $35 million. Cropper et al.'s results suggest that EPA is influenced by pressure from organized interest groups. Comments by environmental groups increase the probability of cancellation. Conversely, comments by growers decrease the probability of cancellation.

The second column in Table 3 shows the coefficients when a linear model of media coverage ($k(c_f) = c_f$) is added to the Cropper et al. model. Coverage of a pesticide in the front section of *The Washington Post* significantly increases the probability that the pesticide is canceled. The other significant variables in the linear media model are producer benefits, evidence of yield loss, reproductive effects, and comments from environmental interest groups. Since none of the cancer risk variables are significant, we cannot calculate the implied value of a statistical life in the linear media model.

It is interesting to compare the results between the Cropper et al. model and the linear media model. Dietary risk and applicator risk are significant in the Cropper et al. model but none of the cancer risk variables are significant in the linear media model. The correlation between the applicator risk variable and the front section media variable is 0.32. The correlation between the dietary risk variable and the front section media variable is 0.19. Thus in the Cropper et al. model, some of the effects of the media may have been picked up by the cancer risk variables. To test if media coverage completely overwhelms cancer risk considerations, we conducted joint significance tests for the cancer risk variables in linear media model. Consider the null hypothesis that the decision is not a function of any cancer risk information (the second through seventh variables in Table 3). This hypothesis is rejected at the 0.05 level by a likelihood ratio test, but is not rejected by a Wald test.

Table 3. Estimation results for probit model of EPA pesticide cancelation decisions

Variable	(1) Cropper et al. (1992)		(2) Linear media model		(3) Exponential media model	
Intercept	–1.824	(.785)	–3.268	(1.102)	–3.614	(1.101)
Diet risk × (1-diet missing)	.004[a]	(.002)	7.3E-4	(.003)	7.7E-5	(2.5E-4)
Diet missing	–.775	(.540)	–1.341	(.714)	–2.004[a]	(.802)
Applicator risk × (1-applicator missing)	6.7E-4[a]	(2.7E-4)	1.9E-4	(3.3E-4)	4.7E-6	(3.3E-4)
Applicator missing	–.529	(.630)	–1.330	(.828)	–1.356	(.891)
Mixer risk × (1-mixer missing)	1.5E-4	(.014)	.004	(.014)	.007	(.013)
Mixer missing	.540	(.683)	1.371	(.881)	1.367	(.935)
Producer benefits[b] × (1-benefits missing)	–.066[a]	(.025)	–.083[a]	(.031)	–.090[a]	(.032)
Benefits missing × yield loss	–2.413[a]	(.446)	–2.456[a]	(.445)	–2.555[a]	(.449)
Benefits missing × (1-yield loss)	–.934	(.789)	–1.767	(1.059)	–2.007	(1.115)
Reproductive effects	1.026[a]	(.518)	2.411[a]	(.956)	2.777[a]	(.943)
Danger to marine life	–.283	(.702)	.325	(.885)	.608	(.974)
Academics comment	–1.333	(.753)	–.966	(.979)	–.860	(1.014)
Growers comment	–1.829[a]	(.762)	–2.283	(1.213)	–3.006[a]	(1.353)
Environmental groups comment	3.398[a]	(.604)	2.438[a]	(.732)	3.985[a]	(.812)
Front section *Washington Post*[c]	. . .		.536[a]	(.212)	. . .	
Exp(Front section *Washington Post*)	. . .		. . .		0.0122[a]	(.004)
Log likelihood	–46.0		–39.7		–36.4	

Note. Standard errors appear in parentheses to the right of coefficients; Sample size = 242.
[a]Significant at the .05 level; [b]Millions of dollars; [c]Thousands of words.

Since these results are ambiguous, we should not rule out the possibility that EPA is influenced by both cancer risk information and media coverage.

Continuing the comparison between the first two columns in Table 3, we see that the producer benefit and yield loss variables are significant in both models. The conclusion that EPA considers both qualitative and quantitative producer benefits does not change when media coverage is included as an independent variable. The reproductive effects variable is significant in both models. Comments from environmental groups are significant in both models, but comments from growers are significant only in the Cropper et al. model. The correlation between the growers variable and the front section media variable is –0.08, so it is not likely that much of the effects of the media were picked up by the growers variable in the Cropper et al. model. As shown below, the growers variable is significant in the non-linear media models. Furthermore, the growers variable would be significant in the linear model at the ten percent level. Hence it appears that, even when we control for media coverage, interest group comments are significant determinants of EPA pesticide decision making.

The linear media model suggests that media coverage is an additional determinant of EPA decision making. It is difficult to give a precise interpretation to the coefficient of the media variable because we are measuring the net effect of the media. It is possible that media coverage leads many citizens to form the opinion that the pesticides should be canceled. It is also possible that the EPA places more weight on opinions that are in favor of cancellation. Although further study is needed to separate the effects of preferences and salience, we can make some tentative conclusions by assuming that the EPA places approximately equal weight on positive and negative opinions. If this assumption is indeed true, then as a result of media coverage, many people formed the opinion that the pesticides should be banned. Furthermore, it may be the case that media coverage is biased toward risk and away from benefits. The observed pattern of media coverage supports such a hypothesis. As noted above, media coverage is correlated with cancer risks. In addition, media coverage is essentially uncorrelated with producer benefits. Perhaps stories about the cancer risks of pesticides are more appealing to the media than stories the benefits of pesticide use.

To test whether the media effect is non-linear, we performed a regression which utilized the exponential function for media coverage ($k(c_f) = \exp(c_f)$). The coefficients are shown in the third column of Table 2. The coefficient of the exponential function is significant and the log likelihood for the non-linear model is greater than the log likelihood for the linear model. This suggests that the effect of the media is indeed non-linear. The exponential model implies that media coverage is extremely powerful when coverage levels are high. The results for the other coefficients are similar to those found in the previous two models with one important exception. The diet missing variable is significant in the non-linear media model. This implies that, when information about diet risks is missing, EPA is less likely to cancel the pesticide. Conversely, when evidence exists that using the pesticide creates cancer risks, EPA is more likely to cancel the pesticide. Since the coefficient of the diet risk variable itself is not significant, the magnitude of the risk does not appear to be an important determinant of EPA decisions. One interpretation of this result is that when a quantitative risk estimate exists, interest groups can use this to their advantage, regardless of the magnitude of the risk. For example, an interest group that is opposed to a pesticide could point to the expected deaths that will result if the pesticide is used to buttress their arguments for cancellation.

To test the robustness of the non-linear model, we performed two additional non-linear regressions. First we used a cubic function for media coverage rather than the exponential function ($\eta k(c_f) = \eta_1 c_f + \eta_2 (c_f)^2 + \eta_3 (c_f)^3$). With the exception of the reproductive effects dummy variable, the variables that are significant in the exponential media model are also significant in the cubic media model. The magnitude of the estimated third order polynomial for media coverage is very small when coverage is low, and increase dramatically when coverage passes a threshold of about 5000 words. Next we used a piece-wise linear spline function for media coverage. We allowed the slope of the spline function to change at the "knot", or threshold, of 5000 words. (See Greene, 1993, for more details on spline regressions.) All the variables that are significant in the exponential media model are also significant in the spline model. The coefficient on the function defined for media coverage less than 5000 words is insignificant and the coefficient on the function defined for coverage greater than 5000 words is positive and significant. This implies that media coverage has no effect when coverage is low and a positive effect when coverage is high.

Taken together, the results of all three non-linear regressions are strong evidence that media coverage has non-linear effects on EPA decision making. Media coverage is particularly important when coverage levels are high. Furthermore the non-linear models reinforce the basic conclusions from the linear media model. Media coverage is best viewed as an additional determinant of EPA pesticide decision making. EPA balances economic impact, organized interest group pressure, media coverage, and risk information when deciding whether or not to cancel a pesticide.

4. Conclusion

The theory presented in this paper predicts that media coverage will affect public opinion, and that bureaucratic decision makers will respond to public opinion. Although we did not directly measure public opinion, the statistical analysis of EPA pesticide regulation verifies a link between media coverage and EPA decisions. Our results offer preliminary evidence that public opinion has a systematic effect on EPA decision making. Including media coverage as an explanatory variable does not change the conclusions found by Cropper et al. with respect to economic impacts and organized interest groups. But we do offer a slightly different interpretation of the effects of cancer risk assessment. EPA is apparently concerned about whether or not cancer risks have been quantified, but the exact magnitude of the risks does not appear to be an important consideration.

It is interesting to note that three of the most widely covered pesticide decisions (DDT, Alar, and EDB) are essentially not included in the statistical analysis. The DDT crisis occurred before the study period. In the case of Alar, Congress took direct action, effectively bypassing the normal regulatory procedure. The special review was eventually completed and Alar was canceled, but long after Alar had been removed from the market. Although EDB is in the pesticide data base, the major crisis occurred after EPA's "final" decision in 1983. Even without including these obvious cases, we are able to detect the influence of the media.

In the revealed preference model considered in this paper, media coverage is an exogenous variable. Future work might include a model where media coverage is determined endogenously by the actions and interactions of organized interest groups, politicians, media editors, and the general public. For example, politicians may use the congressional hearings process and other means to influence the media's coverage of various public policy issues. Furthermore, organized interest groups may seek the most effective tradeoff between the amount of resources spent on lobbying and the amount of resources spent trying to enlist the media to further their policy agenda. Thus it may be fruitful to incorporate the media into more general political economy models.

References

Bennet, L. (1988). *News: The politics of illusion*. New York: Longman.

Baumgartner, F. and Jones, B. (1993). *Agendas and instability in American politics*. Chicago: University of Chicago Press.

Brennan, G. and Buchanan, J. (1984). Voter choice: Evaluating political alternatives. *American Behavioral Scientist* 28: 185–201.

Cropper, M., Evans, W., Berardi, S., Ducla-Soares, M. and Portney, P. (1992). The determinants of pesticide regulation: A statistical analysis of EPA decision making. *Journal of Political Economy* 100: 175–197.

Graber, D. (1993). *Mass media and American politics*. Fourth edition. Washington DC: CQ Press.

Greene, W. (1993). *Econometric analysis*. Second edition. Englewood Cliffs: Prentice Hall.

Gupta, S., Van-Houtven, G. and Cropper, M. (1996). Paying for permanence: An economic analysis of EPA's clean-up decisions at superfund sites. *Rand Journal of Economics* 27: 563–582.

McFadden, D. (1975). The revealed preferences of a government bureaucracy: Theory. *Bell Journal of Economics* 6: 401–416.

McFadden, D. (1976). The revealed preferences of a government bureaucracy: Empirical evidence. *Bell Journal of Economics* 7: 55–72.

Smith, R. and Blundell, R. (1986). An exogeneity test for a simultaneous equation tobit model with an application to labor supply. *Econometrica* 54: 679–685.

Taubes, G. (1995). Blowup at Yucca Mountain. *Science* 268: 1836–1839.

Thomas, L. (1988). Revealed bureaucratic preference: Priorities of the consumer product safety commission. *Rand Journal of Economics* 19: 102–113.

Van-Houtven, G. and Cropper, M. (1996). When is a life too costly to save?: The evidence from U.S. environmental regulations. *Journal of Environmental Economics and Management* 30: 348–368.

Weingast, B. and Moran, M. (1983). Bureaucratic discretion or congressional control?: Regulatory policymaking by the Federal Trade Commission. *Journal of Political Economy* 91: 765–800.

Wood, W. (1985). The educational potential of news coverage of economics. *Journal of Economic Education* 16: 27–35.

Yates, A. (1993). Risk assessment, risk communication, and the media: The case of Alar. Working Paper 93-7, Political Economy Research Center, Bozeman, MT.

Yates, A. (1997). Should risk assessment be separated from risk management?: An analytical model. Working Paper, Department of Economics, Wake Forest University.